TIME VARYING CORRELATION RESEARCH AMONG CORN, ETHANOL, AND GASOLINE: COPULA –GARCH APPROACH

A Thesis

by

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ABSTRACT

Ethanol is a renewable source made mostly from corn starch, and nearly 97 percent of gasoline contains ethanol in the USA. Corn for producing ethanol increased its production from 3 billion bushels in 2007 to over 5 billion bushels, which is almost 32 percent of total corn consumption in 2015. Over past decade, the biofuel expansion has impacted the price of agricultural goods and energy markets. This has incited a debate among researchers, so there are numerous studies about the price connection between biofuel and farming products. Despite some agreement on the relationship between ethanol production and the price of agricultural goods, most studies noted the wide range of estimates of the effect of biofuel on the energy market. The goal of our examination is to analyze the time-varying correlation and the dependence structure among corn, ethanol and gasoline markets. Our research method uses price data only. This paper does not create other variables deliberately because other research approaches with additional variables have estimated a wide range of results. We focus on the price data itself. Thus, we will apply Copula-GARCH model as a time series approach to design the time-varying correlation and the structure of dependency. The C-Vine Copula are made up of the three pairs which include Ethanol-Corn (E, C), Ethanol-Gasoline (E, G), and Corn-Gasoline given ethanol (C, G lE). The Clayton Coupla was picked to describe the dependence of Ethanol-Corn (E, C) with the parameter value of 0.1979 and Kendall's tau correlation of 0.0892. Likewise, the Clayton Copula is the best for estimating the pair of Ethanol-Gasoline (E, G) with the parameter value of 0.3522 and the Kendall rank correlation of

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0.1492. The conditional copula of Corn-Gasoline given ethanol (C, G lE) chose the Rotated Clayton 180 degree. The estimate of the copula is 0.0517, and the Kendall rank correlation is 0.0252. According to our research findings, there are weak price correlations between corn and ethanol after implementation of the Energy Independence and Security Act of 2007.

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1. INTRODUCTION

Ethanol is a renewable energy made mostly from corn starch, and nearly 97 percent of gasoline contains ethanol in the USA (U.S. DOE, 2016). The production of ethanol in the U.S. was approximately 6.5 billion gallons in 2007 and, it was increased to 15 billion gallons in 2015 (RFA, 2016). Corn for producing ethanol has also been increased from 3 billion bushels of 2007 to over 5 billion bushels which are almost 32 percent of total corn consumption in 2015 (USDA ERS, 2016). The main reason for ethanol production increase is the U.S. Renewable Fuel Standard (RFS) which requires fuel suppliers to mix renewable fuel within gas and diesel. They set blending renewable energy with 9 billion gallons in 2008, and it was expected 36 billion gallons until 2022. Initially, they expected that the production of cellulosic ethanol would be increased up to 16 billion gallons in 2022 to avoid pressing the crop price upward. However, making cellulosic ethanol is more challenging than using starch-based crops because they have still technical problems to reduce production cost. Therefore, recent production of cellulosic ethanol was just around 140 million gallons in 2015 (EPA 2016).

Corn accounts for more than 95 percent of feed grain production in the U.S. Corn cultivation is concentrated in the Midwest, with the states of Illinois, Nebraska, and Minnesota the top producing states. Since 1996, when U.S. farm policy changed to allow more flexibility in farmers' planting decisions, planted corn acreage has ranged from 76 million acres to 97 million. Over that same period of time, corn production has risen from 9 billion bushels to 14 billion bushels in 2015 (USDA ERS, 2016). Corn production has

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mounted over time due to improvements in technology such as fertilizers, seed variation, pesticides, and machinery and production practices.

The gasoline is the essential item in the U.S. Especially, the price of gasoline has been changed dramatically during last 2years. This is because the production of the U.S shale oil is rapidly increasing as a primary source of energy. The advancement of the technology of hydraulic fracturing and horizontal drilling has led gasoline to the primary energy source in US (USGS, 2016). The light tight sand oil from shale gas is quickly evolving as a significant low-cost energy which is unique resource in US (PWC, 2013). Swift production growth in the light tight sand oil is having dramatic effects on gasoline pricing in the U.S. The US domestic gas price has already decoupled from global indices and imports are forecast to keep small gasoline price (EIA, 2016).

Over past decade, the biofuel expansion has impacted the price of agricultural goods and energy markets. This has incited a debate among researchers, so there are numerous studies about the price connection between biofuel and farming products. Zhang et al. (2009) examined the price volatility related to corn, biofuel, soybean, and gasoline. They find that gas price had an influence on both ethanol price and oil, and increased ethanol price had a short-term effect on the price of an agricultural commodity. The National Research Council (2011) analyzed the contribution of biofuel on the growing of corn price from 2007 to 2009. The result of these estimates is from 17 percent to 70 percent. Sera et al. (2011) assessed the price connection of maize, ethanol, gas, and oil in US from 1990 to 2008. They found that the ethanol market had a strong connection with maize and energy retails. Moreover, the ethanol value surges caused the growth of both maize value

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and gas. Meyer at al. (2012) found that biofuel production changes by the RFS caused the demand increase and raised crop price from the -1 percent to 12 percent according to options data. Chen at al. (2012) explored the price link between the biofuel policies and food markets. They found that corn price increased from 24 percent to 52 percent by their scenarios. Knittel et al. (2015) commented that the ethanol production had a low correlation with gasoline price.

Despite some agreement on the relationship between ethanol production and the price of agricultural goods, most studies have noted the wide range of estimates on the effect by biofuel and energy market. Therefore, some researchers studied why the result of estimation variety. National Research Council (2011) reported that the variations among researches make it difficult to analyze the result with accuracy. Zhang et al. (2013) examined the nine kinds of research on biofuel and energy market expansion on an agricultural commodity. They found that several differences such as model structure, scenario design, the price of crude oil, land supply, the by-product from the use of corn ethanol and the elasticity of replacement between oil and biofuels. Even though the nine studies had real impacts on the values and production among variables, they stopped the quantitative analysis because they identified a lot of essential pieces of knowledge gaps and uncertainties. Persson (2014) conducted more variety of assessment with over one hundred reporting studies about price influences of biofuel on farming products in the USA, EU and the rest of world. The author also reported similar results that there was the bulk of variation on estimations because of model structure and many different assumptions. Recently, Condon et al. (2015) carried out the meta-analysis regarding the

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biofuel impact on agricultural commodity price. The author tried to overcome the difficult comparison among the studies with strict scope focusing on corn and the US biofuel policy. Their results showed that approximately 3 to 4 percent climb in corn values were led by the expansion of 1 billion gallons of ethanol production from the corn in 2015, and the change of the corn price will be smaller in the future.

Furthermore, Condon et al. (2015) also commented that there were not enough correlation researches between biofuel production and crop prices. Kairala et al. (2015) found that the studies about a price relationship within energy values and agricultural goods were a rare even though the issue has noteworthy attention amid researchers afterward carrying the Energy Independence and Security Act of 2007. They claimed that most correlation research between energy values and farming commodities used the univariate process and the linear correlation approaches. The author tried to overcome the limitation of the linear correlation method, then used copula approach as the non-linear method of estimation, and concluded that agricultural goods and the future price of energy had the high correlation and significant relationship.

The goal of our examination is to analyze the time-varying correlation and the dependence structure among corn, ethanol and gasoline markets. This is because Condon et al. (2015) and Kairala et al. (2015) identified that there were few studies about the correlation concerning energy values and farming goods, and most research work with the univariate technique and linear correlation coefficient method. Thus, we will apply Copula-GARCH model as a time series approach to design the time-varying correlation and the structure of dependency.

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Our research method used only price data. This paper did not create other variables deliberately because other research approaches with additional variables have estimated a wide range of results. As NRC (2011) and Zhang et al. (2013) pointed out the grounds for a broad range of estimated prices of agricultural products by the models and the challenge in comparing the result with some precision, the result of our study might reduce some of the confusion about price dependencies among corn, ethanol, and gasoline.

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2. METHODOLOGY

2.1 Copula

In our study, we developed the non-linear method for explaining a time-varying correlation and structure dependency among corn, ethanol, and gasoline. As the price of corn, ethanol and gasoline have the properties of time-series data, we newly adopted the copulas with Generalized Autoregressive Conditional Heteroskedastic (GARCH) approach for better understanding the feature of our data.

Checking dependency by the linear correlation, Pearson's correlation coefficient, is a straightforward calculation that just give us the level of dependency between two variables. Blyth (1996) and Embreachts et al. (2003) noted that the Pearson correlation could be too limiting to estimate the dependences under multivariate distribution, and the linear correlation is not invariant over time. Furthermore, the Pearson correlation requires symmetric and elliptical distribution. Lee et al. (2008) commented that both multivariate Gaussian distribution and multivariate student-t distribution mainly used in the econometrics of multivariate cases, but multivariate normal distribution was not compatible with the features of price data such as skewness, high kurtosis, and volatility clustering. It is well known that most price data have non-linear, non-Gaussian, and asymmetric properties. Thus, measurement by the linear correlation may bring misunderstanding when it applied to non-linear and non-symmetric data. Copula functions can run over these limitations. Sklar (1959) proved copulas that are multi-dimensional joint distribution will be disintegrated toward its multi-dimensional marginal distributions and dependence structures so that copulas can link marginal distributions to multivariate

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distribution functions which can be disintegrated to its univariate marginal distributions. The definition of copula and Sklar theorem, and the property of copulas are given as follows Lee et al. (2008)

2.2 Definition of Copula

The bivariate function C means $[0,1]^2 \rightarrow [0,1]$. This is the copula if it captures c(v_1, v_2) = 0 for v_1=o or v_2=0 and c(v_1,1) = u_1, c(1, v_2,) = u_2 for all v_1, v_2 in [0,1] (the condition of boundary) and $\sum_{i=1}^{2} \cdot \sum_{j=1}^{2} (-1)^{i+j} C\left(v_{1,i}, v_{2,j}\right) \geq 0$ for all $\left(v_{1,i}, v_{2,j}\right)$ in $[0,1]^2$ with $v_{1,1} < v_{1,2}$ and $v_{2,1} < v_{2,2}$ (the condition of monotonic).

2.3 The Theorem of Sklar

F_{12} is the function of joint distribution with margins F_1 and F_2. Next this is a copula C such as z_1 and z_2,

$$F_{12}(z_1, z_2) = C(F_1(z_1), F_2(z_2)) = C(v_1, v_2) \tag{1}$$

On the other hand, C is the copulas and F_1 and F_2 are the function of marginal distributions, the established F_{12} the joint distribution function by marginal F_1 and F_2. ■

The function of joint density f_{12} (z_1, z_2) defined as

$$f_{12}(z_1, z_2) = \frac{\partial^2 F_{12}(z_1,z_2)}{\partial z_1\, \partial z_2} = \frac{\partial^2 C(v_1,v_2)}{\partial v_1\, \partial v_2} \cdot \frac{\partial F_1(z_1)}{\partial z_1} \cdot \frac{\partial F_2(z_2)}{\partial z_2}$$

$$= c(f_1(z_{1,}), f_2(z_2)) \cdot f_1(v_1) \cdot f_2(v_2), \tag{2}$$

here copula density is c(v_1, v_2) = $\frac{\partial^2 c(v_1,v_2)}{\partial v_1\, \partial v_2}$. For independent copula C($u_1 \cdot u_2$)) = 1.

The significant attribution of copulas is the invariance underneath increasing and continual transformation like log transformation.

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From the (2) the log-likelihood function for $\{x_t\}_{t=1}^{n}$ is:

$$\mathcal{L}^x(\theta) = \sum_{i=1}^{n} lnf_{1,t}(z_{1,t}, z_{2,t}; \theta)$$

$$= \sum_{i=1}^{n} lnf_1(z_{1,t}\ ; \theta_1) + \ lnf_2\ (z_{2,t}; \theta_2) + \ln c\ (F_1(z_{1,t}; \theta_1),\ F_2(z_{2,t}; \theta_2); \theta_3)$$

where $\mathcal{X}$ is the observation numbers and θ = (θ_1', θ_2', θ_3') are the parameter of the marginal densities $f_1(\cdot)$ and $f_2(\cdot)$. The log-likelihood is separated into two sections. The first two sections are linked with the marginal, and the last part is connected to the copula. When the maximum likelihood estimation is carried out in a multivariate case, the optimization method will face problems regarding the massive calculation and estimation correctness. Therefore, we apply two-step estimation process to measure the parameters from the copula-GARCH approach. Joe (2005) provided the evidence that this estimator should be asymptotically similar to the maximum likelihood approach under some general requirements.

Patton (2006) commented that copulas could measure the correlation of multivariate and structure of the dependency on non-linear and non-normal distribution. Patton (2006) also claimed that copulas could treat the dependence of extreme cases. Patton (2006) and Jondeau et al. (2006) introduced Copula – GARCH model to explain time-varying dynamic parameters in the financial econometrics, so copula – GARCH can provide time-varying conditional correlation over time.

2.4 Vine Copula

The computation of copula with high dimension is a tough work because of many variables, and Gaussian copula cannot be manageable in high dimension. Furthermore, some copula does not support for various dependence structures between couples of

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variables. Bedford et al. (2001, 2002) reported that Vine copulas could overcome these restrictions. Vine copulas confirmed to be the pliable instrument in high dimensional dependences with the graphical model.

Aas et al. (2009) presented c-vine copula for handling some difficulties by computation of multivariate copulas with pair-relation method. The authors suggested that forming C-vine copula may be beneficial when we recognize the key variable that rules the interactions. The properties of copulas are given as follows Aas et al. (2009)

Let X = (z_1, z_2, z_3) ~ $\mathcal{F}$ with marginal distributions $\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3$ and their density functions f_1, f_2, f_3. The density function of C-vine copula is

$$f(z_1, z_2, z_3) = f(z_1) \cdot f(z_2) \cdot f(z_3) \cdot\ c_{1,2}(F_1(z_1), F_2(z_2)) \cdot\ c_{1,3}(F_1(z_1), F_3(z_3)) \cdot c_{2,3|1}(F_{2|1}(z_2|z_1),\ F_{3|1}(z_3|z_1)) \quad (3)$$

where $c_{1,2}$, $c_{1,3}$, and $c_{2,3|1}$ indicate the densities of bivariate copula $C_{1,2}$, $C_{1,3}$, and $C_{2,3|1}$. $F_{2|1}$ and $F_{3|1}$ are the conditional marginal distribution that can be obtained from (3). The example of the conditional marginal distribution is

$$F_{2|1}(\mathcal{X}_2|\mathcal{X}_1) = \frac{\partial C_{2,1}(F_2(x_2), F_1(x_1))}{\partial F_1(\mathcal{X}_1)}$$

2.5 ARMA-GARCH Model

To use the copulas, it is required to get the marginal distribution. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) approach is broadly applied to the volatility model in the financial econometrics. The current volatility of price would drive a bigger volatility of future price. Thus, this kind of heteroscedasticity hints the

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autocorrelation in the price variation. Bollerslev (1986) suggested that GARCH model for the heteroscedasticity. However, we adopted the ARMA-GARCH model in this paper because of our data features, skewness, and kurtosis. The residuals from the ARMA-GARCH approach could be converted in the uniform distribution for fitting the copulas. We selected ARMA(1,0)-GARCH(1,1) or ARMA(1,0)-GARCH(1,1) by the skewed Student t distribution for the residual of the marginal distribution by the log-differenced weekly price data of corn, ethanol, and gasoline. The properties of ARMA-GARCH are given as follows Patton (2006)

$$X_t = aX_{t-1} + \mu + \varepsilon_t + \theta\varepsilon_{t-1} \ \forall t \tag{4}$$

$$\varepsilon_t = z_t \cdot \sqrt{h_t},\ z_t \sim \text{the skewed Student t-distribution} \tag{5}$$

$$h_t = \omega_t + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{6}$$

Equation (4) explains ARMA(1,1) where μ is the constant term, and ε_t is a weak white noise term. Equation (5) represent the error variable of the creation between h_t as conditional variance and z_t as the residual term by the skewed Student t-distribution. Equation (6) presents the GARCH (1,1) where α describes the ARCH interpretation and β explains the GARCH interpretation. It means that α has the characteristic of a short-term persistence of shock and β add the long-term persistence of shock($\alpha + \beta$). The GARCH model asks the stationarity of conditional variance, h_t,and the error term, ε_t. According to Nelson (1990), the second- moment condition can check this requirement which is $\alpha + \beta < 1$.

Therefore, it is reasonable to adopt Vine Copula – GARCH model for better

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estimation. ARMA-GARCH or GARCH processes can catch marginal distributions for using vine copula model, then the residual from GARCH process can be changed to the uniform distribution by the empirical distribution function. Finally, we can estimate the structure of dependencies by C-vine copula.

3. DATA DESCRIPTION

We choose the weekly price data of corn, ethanol, and gasoline from Jan, 4th, 2008 to Feb 16th, 2016 to capture the structure of dependency and dynamics among three commodities. We choose the weekly price data of corn, ethanol, and gasoline from Jan, 4th, 2008 to Feb 16th, 2016 to capture the structure of dependency and dynamics among three commodities. We used corn and ethanol data from USDA-AMS, and gasoline data from EIA. There were two weeks of missing values of 432 observations, so we substituted them using cubic spline interpolation. Figure 1 shows us the price movements of three commodities.

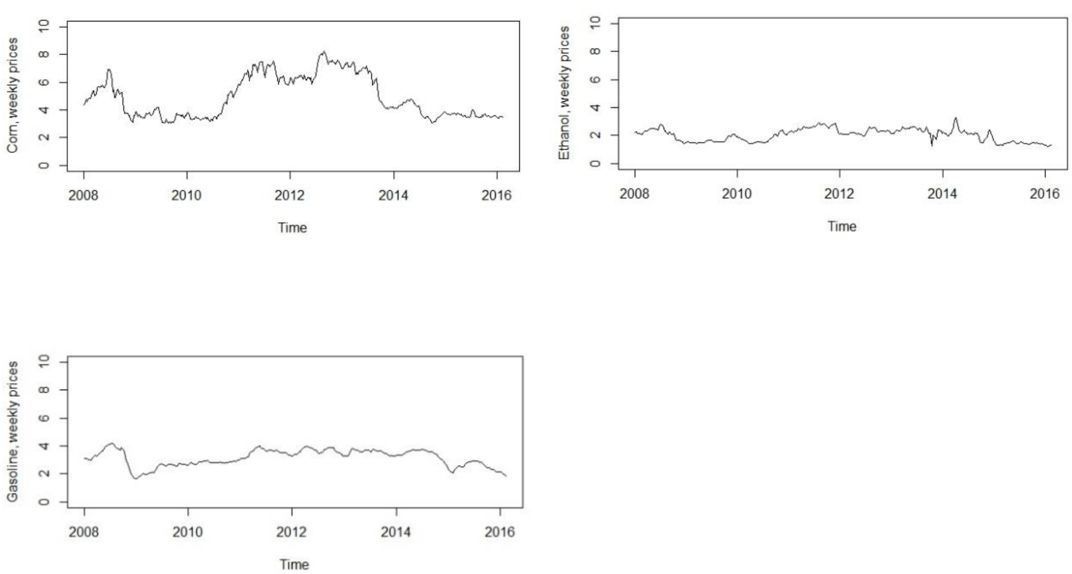

Figure 1. Weekly Close Prices of Corn, Ethanol and Gasoline, Jan 4, 2008 – Feb 12, 2016

First of all, we check the stationarity because these closed price data have a kind of time series property. Table 1 gives us the summary statistics of the unit root test for

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checking the stationarity. According to augmented Dickey-Fuller (ADF) test, all closed price of corn, ethanol, and gasoline are non-stationary. Additionally, Phillips – Perron (PP) test also indicates that the consequences are not dissimilar as of the results of ADF test. However, Elliot, Rothenberg, and Stock (ERS) test show a little different result. The closed corn price is non-stationary, either. Ethanol and gasoline are stationary at five percent of critical level, but these prices are not stationary at one percent level.

Table 1. Unit Root Test for Time Series Property of Weekly Close Prices and Weekly Returns

	AUGMENTED DICKEY-FULLER TEST		**PHILLIPS-PERRON TEST**		**ERS TEST**	
VARIABLES	Test statistics	P-value	Test statistics	P-value	Test statistics	P-value
			A. WEEKLY CLOSE PRICES.			
CORN	-0.666	0.51	-1.440	0.81	-1.298	0.20
ETHANOL	-0.996	0.32	-2.620	0.32	-2176	0.03
GASOLINE	-0.862	0.39	-1.368	0.84	-2.373	0.02
			B. WEEKLY RETURNS.			
CORN	-13.033	< 2e-16	-16.370	0.01	-7.638	1.55e-13
ETHANOL	-14.563	< 2e-16	-15.208	0.01	-8.552	2.38e-16
GASOLINE	-6.943	1.47e-11	-8.112	0.01	-5.791	1.39e-08

Note: ERS Test denotes Elliot, Rothenberg and Stock Unit root test.

Next, we would like to analyze the first log – differenced price data. The logarithmic price data is determined by:

$$Return_t = [lg(p_t) – lg(p_{t-1})] * 100$$

Here, p_t indicates the closed price of the period at t. Figure 2 displays us three returns data over time. Then, we explore the stationarity with returns data by ADF, PP, and ERS test. All test results suggest that three returns data are stationary at one percent of critical level.

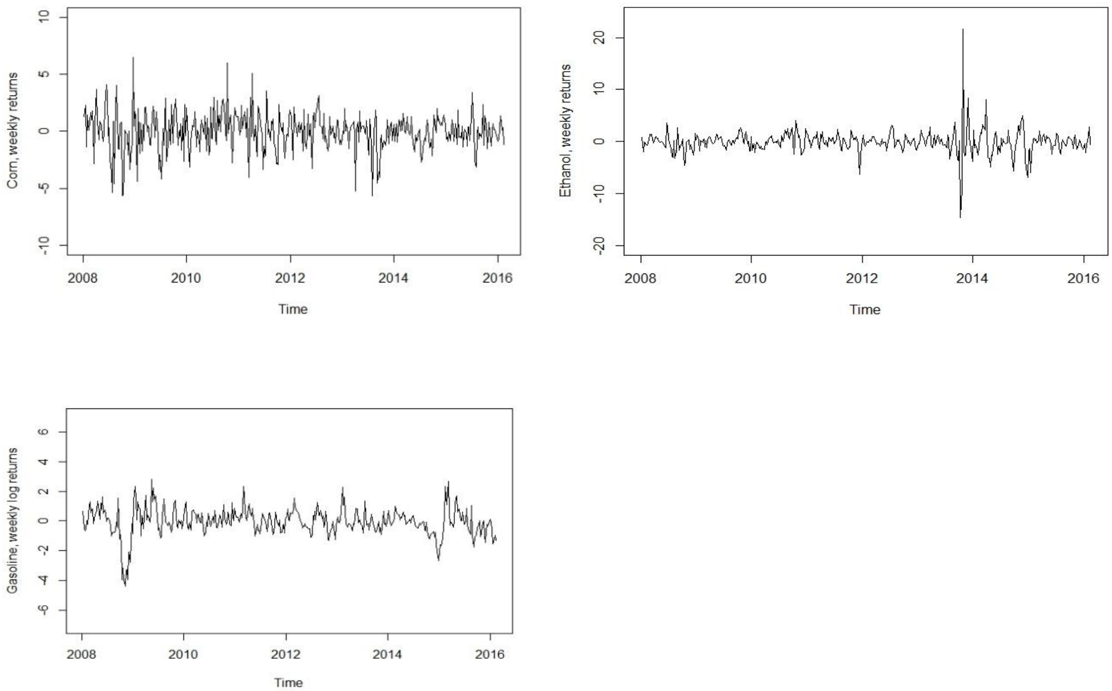

Figure 2. Weekly Returns of Corn, Ethanol and Gasoline, Jan 4, 2008 – Feb 12, 2016

Table 2 provides the descriptive statistics of log-differenced prices. As presented in this results, the means of three commodities are nearby to zero, and the standard deviations could be a little bit small. These convey that three returns prices are not constant and around the mean. The skewness means that corn and gasoline prices are negative, but ethanol price is positive. The kurtoses of three prices are positive. The meaning of positive skewness involves that the ethanol price has only the longer right tail of density in the price change. It designates that the ethanol price may be more vulnerable when price moves uphill than downhill. This also considerable probability of a negative return. The statistics of kurtosis imply that the distribution of three prices can be said to be leptokurtic. It means that three prices have higher peak probability distribution with heavy tail not than

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the normal distribution. Jarque-Bera test confirms that properties of our data are not normal distribution. ARCH-LM test indicates that these data have a characteristic of ARCH effect, thus it is reasonable using GARCH approach to get marginal distribution from data.

Table 2. Explanation of Data Statistics for Log-difference of Corn, Ethanol, and Gasoline Price

	CORN	**ETHANOL**	**GASOLINE**
MEAN	-0.02	-0.05	-0.05
STD. DEV.	1.65	2.16	0.92
MEDIAN	0.06	0.00	-0.07
MAX	6.44	21.61	2.79
MIN	-5.65	-14.52	-4.39
RANGE	12.09	36.13	7.18
SKEWNESS	-0.29	1.54	-0.80
KURTOSIS	4.78	31.88	6.86
JARQUE-BERA (P-VALUE)	63.1389 (1.943e-14)	15022.6398 (2.2e-16)	312.5083 (2.2e-16)
ARCH-LM (P-VALUE)	8.8661 (0.003)	15.69 (7.46e-05)	213.93 (2.2e-16)
NO. OF OBS.		432	

4. EMPIRICAL RESULT ANALYSIS

4.1 ARMA-GARCH for Marginal Process

Table 3 presents the result of ARMA(1,0) - GARCH (1, 1) and ARMA (1, 1) – GARCH (1,1) by standardized residual for the price changes.

Table 3. Parameter Estimation for Marginal Distribution Model

	CORN	STD. ERROR (P-VALUE)	ETHANOL	STD. ERROR (P-VALUE)	GASOLINE	STD. ERROR (P-VALUE)
MU	-3.81e-02	6.96e-02 (0.58445)	0.02204	0.05700 (0.6990)	0.000489	0.026859 (0.98547)
MA1	-	-	-	-	0.010004	0.083317 (0.90442)
AR1	1.93e-01	4.94e-02 (9.44e-05)	0.48677	0.04517 (<2e-16)	0.661850	0.059465 (<2e-16)
ω	2.72e-06	1.37e-02 (0.99984)	0.25031	0.10106 (0.0133)	0.14432	0.009314 (0.12125)
α	2.36e-02	1.37e-02 (0.8689)	0.29871	0.09713 (0.0021)	0.108678	0.040982 (0.00801)
β	9.74e-01	1.60e-02 (<2e-16)	0.65328	0.07374 (<2e-16)	0.860472	0.050239 (<2e-16)
SKEWNESS	0.90636	6.51e-02 (<2e-16)	1.02106	0.06308 (<2e-16)	1.232345	0.084393 (<2e-16)
KURTOSIS	6.26679	1.51e+00 (0.00011)	3.84277	0.79322 (1.27e-06)	6.095218	1.894524 (0.00129)
LOG LIKELIHOOD	-773.042	-	-716.183	-	-355.959	-
AIC	3.688140	-	3.419306	-	1.720846	-
BIC	3.755118	-	3.486283	-	1.797392	-

Note: ARMA(1,0)-GARCH (1,1) model for corn and Ethanol and ARMA (1,1)-GARCH (1,1) for Gasoline

The skewness parameter of corn is less than 1. Thus, it implies that the residual of corn and ethanol are skewed to left, and it means that significant negative price change is more frequent than large positive price change of the same measurement. However, the value of skewness is almost zero, so there is hardly price change. The skewness coefficient of ethanol and gasoline are more than 1, so this value means that gasoline price has more positive price change during the same periods. The kurtosis of three residuals is greater than 3, expressing that the residuals are not following the normal distribution.

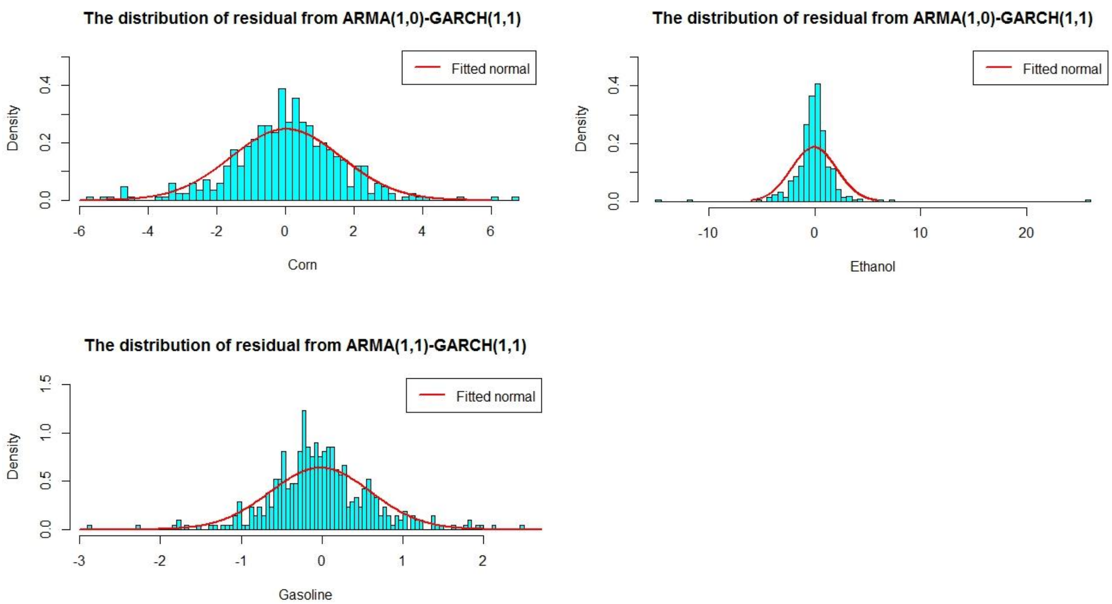

Figure 3. Distributions of Residual from Marginal Process

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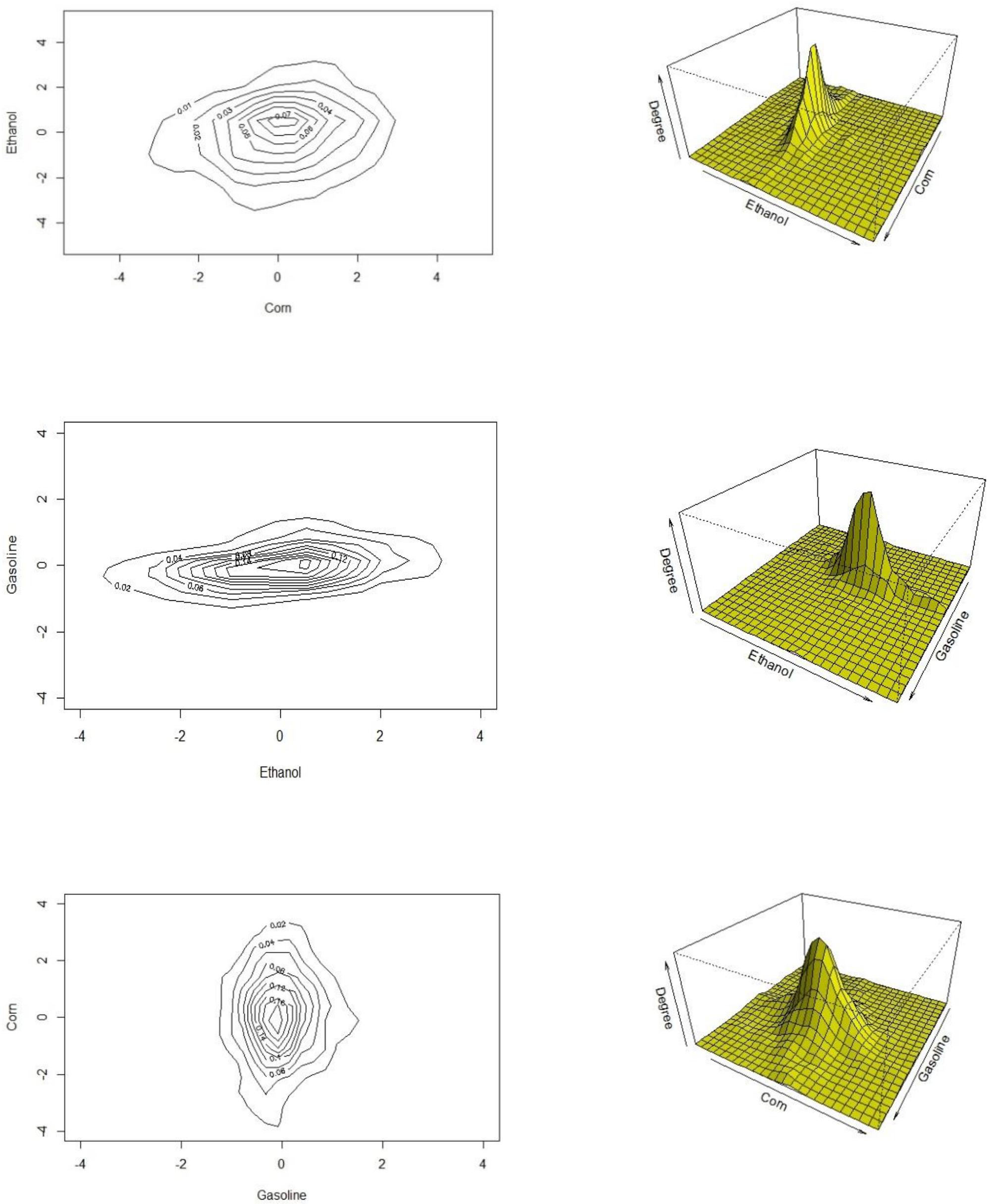

Figure 4. Contours of Residual from Marginal Process

Additionally, Figure 3 and Figure 4 show us the distribution of residuals. These two results can give us the proper distribution which can be modeled in ε_t ~SkT(ν, γ), where ν is skewness and γ are kurtoses. The selection of skewed Student T distribution is

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moderately owing to the expression of three residuals. The values of α, ARCH interpretation, and β, GARCH interpretation, are at significant at 0.1 and 0.001 of critical level. From the results, α + β of three residuals are less than 1. We can interpret this as the volatilities of three prices have a long-run persistence. However, α of corn, ethanol, and gasoline are smaller than their β, so we also describe that short-run persistence of corn and gasoline has a slight impact on price volatility. However, the values of corn are almost zero, we can interpret it exactly.

Table 4. Test of Goodness Fit for Marginal Distribution

	JARQUE–BERA TEST		SHAPIRO-WINK TEST		LJUNG-BOX TEST(Q10)		LJUNG-BOX TEST(Q15)		LJUNG-BOX TEST(Q20)	
	Test Statistics	P-value	Test Statistics	P-value	Test Statistics	P-value	Test Statistics	P-value	Test Statistics	P-value
CORN	70.1305	5.5e-16	0.9788	7.8e-16	9.0769	0.5248	10.2483	0.8038	21.4176	0.3729
ETHANOL	556.591	0	0.9421	8.6e-12	15.8519	0.1039	24.5012	0.0571	30.1231	0.0678
GASOLINE	61.3366	4.7e-14	0.9742	8.1e-07	7.0613	0.7196	18.1777	0.2534	19.4957	0.4898

The proper specification of the marginal distribution of the residuals required for the copulas. Thus, we need to check the serial correlation by Ljung-Box test, and the density specification by Jarque-Bera (JB) test and Shapiro-Wilk (SW) test. In Table 4, the p-value of JB, SW, are significant at 0.01 of critical level, and Ljung-Box test are not significant at 0.05 of critical value. This means that these data are no correlation and independently distributed. Therefore, the marginal distribution is well specified before using the copulas. Thus, we can convert the standardized residuals by the marginal process to the uniform distribution [0, 1] by means of the empirical distribution function.

From the residual of GARCH model, we can check the dynamic correlation over

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time. Figure 5 show us that the correlation of corn, ethanol, and gasoline has the time-varying correlation. Thus our approach by copula would be one of the good approaches.

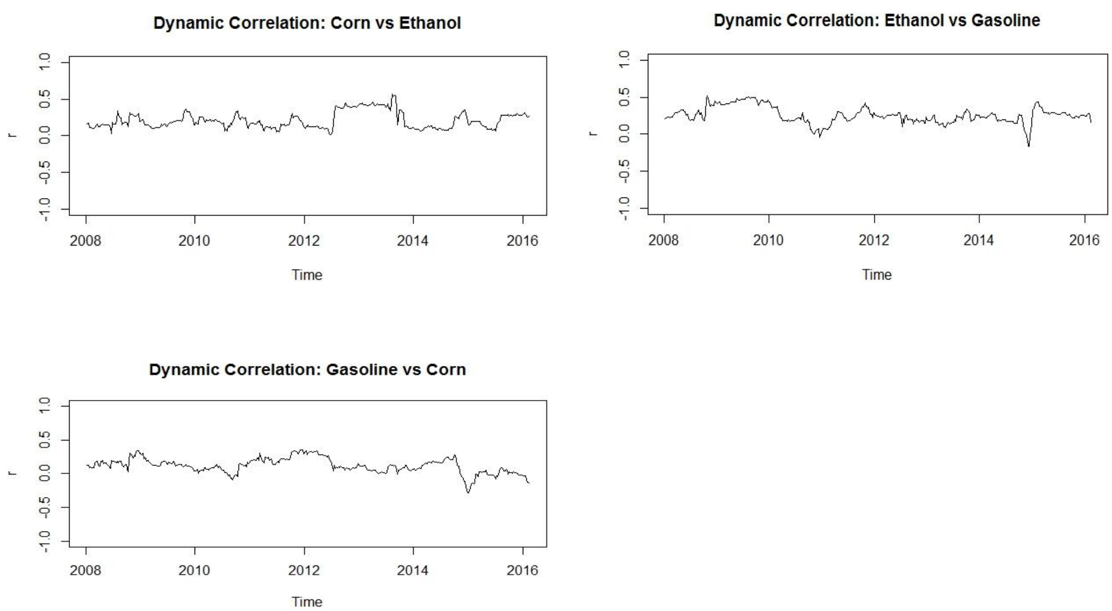

Figure 5. Dynamic Pearson Correlation among Corn, Ethanol, and Gasoline by Exponentially Weighted Moving Average (EWMA) Model

4.2 Consequences of C-vine Copula

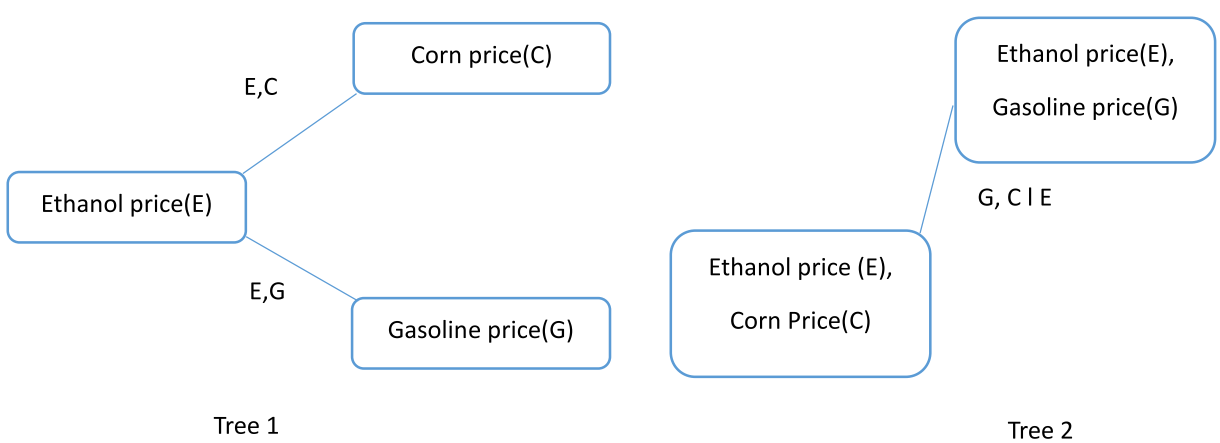

Figure 6. Three-dimensional C-vine Trees for the Pair-copulas

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We employ the C-vine copula to examine the structure of dependency among corn, ethanol, and gasoline prices. The ethanol is the key variable in our study because the ethanol has demand factor on the corn, and it has supply factor on the gasoline.

Figure 6 present three-dimensional C-vine tree graphs. Left tree consists of Ethanol price- Corn price (E, C) and Ethanol price-Gasoline price (E, G). The right tree shows us the conditional pair-copula which is Corn price-Gasoline price given Ethanol price (C, GlE). The copula estimation works with the maximum likelihood method and the joint likelihood function. We select the Clayton copula for the first pair of ethanol and corn and the Clayton copula for the second pair of ethanol and gasoline. The Rotated Clayton copula will be chosen for the third conditional pair of corn and gasoline given ethanol. All three copulas are selected by Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) for the finest estimation. The parameters from copulas have to be converted to Kendall's tau correlation because each copula has different parameter ranges. As Kendall's tau correlation has the interval from -1 to 1 and the property of measuring the concordance, we can easily compare the structure of dependencies.

Table 5. C-vine Copula by the Maximum Likelihood Method

Tree#	**Pair-Copula**	**Selected Copula**	**Parameter (p-value)**	**Kendall Rank**	**AIC**	**BIC**
1	E,C	Calyton	0.1979 (0.000)	0.0892	-9.031935	-4.9846
	E,G	Clayton	0.3522 (0.000)	0.1492	-28.08951	-24.0421
2	(C,G) ׀E	Rotated Clayton 180º	0.0517 (0.000)	0.0252	1.056342	5.1038
	C,G	Gaussian	0.0868 (0.0000)	0.0409	-1.047168	3.0002

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Table 5 hand out the estimation result of C-vine copulas, the Ethanol price-Corn price (E, C), Ethanol price-Gasoline price (E, G), and the Corn price-Gasoline price give the Ethanol price (C, G lE). The first result indicates that the best copula function for the Ethanol price - Corn price is the Clayton copula by the smallest AIC and BIC. The parameter from the Clayton copula is 0.1979, and the Kendall rank correlation is 0.0892. It suggests that when the ethanol price upsurges, the corn price also increases, and with the ordered reversed. Nevertheless, it is a feeble and positive price dependence in this couple relation, so the price movement of the ethanol is a little related to the corn price with the order reversed.

The second outcome, the Ethanol price-Gasoline price, has been calculated by the Clayton copula. The estimation parameter is 0.3522, and the Kendall rank correlation suggests 0.1492. These numbers suggest that when the ethanol price increases, the gasoline prices increase with the ordered reversed. This relation also has a feeble and positive price dependence like the Ethanol price-Corn price.

The third result is the estimation of a conditional pair-copula of the Corn price-Gasoline price given the ethanol price (C, G lE). The rotated Clayton 180-degree copula provide the best estimation. The parameter is 0.0517, and the Kendall rank correlation shows 0.0252. Even though the conditional pair-copula has a real dependence, the price co-movement is feeble.

Figure 7. Trees from the Estimation of C-vine Copula with Used Copula Family and Kendall's Tau Correlation

As reported by our simulation, the parameter from copulas and the Kendall rank correlation of the conditional pair-copula (C, G lE) are smaller than the unconditional estimation result of pair-copula (C, G), 0.0868 of the parameter and 0.0409 of correlation. This comparison involves that the ethanol price has an impact on the price connection between the corn price and the gasoline, but the influence of ethanol price is brittle.

Without considering the property of price data, we could misunderstand the exact price relations among variables. Table 6 show us that the value of Kendall's tau are higher than our research result.

Table 6. Kendall Rank Correlation from Weekly Closed Price

	CORN	**ETHANOL**	**GASOLINE**
CORN	1	0.5763476	0.5008576
ETHANOL	0.5763476	1	0.5734629
GASOLINE	0.5008576	0.5734629	1

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5. CONCLUSION, IMPLICATION, AND SUGGESTION

In this paper, we focused on examining the structure of dependence among corn, ethanol, and gasoline. Thus, we formed two-dimensional a C-Vine Copula-GARCH approach. To estimate for a structure of dependence, we shaped the marginal distribution using an ARMA-GARCH process with skewed student t distribution. The C-Vine Copula was applied to explain the relationship structure among marginal method. The observed results of ARMA-GARCH process confirmed that the price structure of corn and gasoline have a strong long-term persistence in the volatility, but the ethanol price has a stronger short-run persistence in volatility even though it also has the characteristics of a long-run persistence. This result can be interpreted that ethanol market has a weak price structure.

The C-Vine Copula are made up of the three pairs that are Ethanol-Corn (E, C), Ethanol-Gasoline (E, G), and Corn-Gasoline given ethanol (C, G lE). The Clayton Coupla was picked to describe the dependence of Ethanol-Corn (E, C) with the parameter value of 0.1979 and Kendall's tau correlation of 0.0892. Likewise, The Clayton Copula is the best for the estimation the pair of Ethanol-Gasoline (E, G) with the parameter value of 0.3522 and the Kendall rank correlation of 0.1492. The conditional copula of Corn-Gasoline given ethanol (C, G lE) chose the Rotated Clayton 180 degree. The estimation of the copula is 0.0517, and the Kendall rank correlation is 0.0252. The unconditional copula estimation of Corn-Gasoline selected the Gaussian copula with the parameter value of 0.0868, and the Kendall rank is 0.0409.

From the result of our study, it can be determined that the price relationship

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between corn and ethanol is weak by the Kendall rank correlation of 0.0892. Even though ethanol has the major increasing portion of corn consumption, other consumptions such as the use of feedstock for livestock and the exportation of corn have been decreased. Furthermore, the ending stocks of corn maintain about one to two billion bushels every year. These demand and supply factors can explain the low price correlation within corn and ethanol.

The price relationship both ethanol and gas is also weak due to the Kendall rank correlation of 0.1492. Although the ethanol mandate is still the reason for the consumption of the ethanol, the ethanol hardly becomes the substitute for the gasoline because the gasoline is well known as a relatively inelastic commodity, and the popularity of the shale gas make the gasoline price cheaper than the ethanol price. Another reason is that the daily consumption of gasoline has not been raised from 390 million gallons per day in 2007 to 384 million gallons per day in 2015. As gasoline consumption is stable, this could explain the weak price correlation between ethanol and gasoline.

The price relationship between corn and gasoline is almost nothing according to the estimations result of C-Vine copula that the conditional correlation is 0.0252, and the unconditional correlation is 0.0409. This result means that the price of gasoline and corn does not affect each other in the market.

Opponents of ethanol mandates have several concerns, forcing up the food price and feed cost, more nitrogen dioxide, and a corrosive toll on the two cycles engine to repeal the Renewable Fuel Standard. My research could not explain some technical issues, but could tell the price problem related to ethanol mandates. According to my research

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finding, there are weak price correlations between corn and ethanol after implementation of Energy Independence and Security Act of 2007. [1] Therefore, the United States Environmental Protection Agency does not need to reduce or abolish ethanol mandates by the criticism of increasing food price and feeding cost.

In future research, we need to compare our findings directly with linear methods to show how these results may differ. Also, the study might be improved by breaking the time series into two parts, the ethanol expansion phase, and industry maturity phase, to see if the correlations changed as the industry matured. It might also be helpful to expand the time series to include a few years before implementation of RFS, and analyze specifically the differences of price correlations.[2][3]

[1] Dr. David Bessler comments that the most of our research summarizing the probability relationship between these three variables which are con price, ethanol price, and gasoline price. To take further steps, it needs to do causal relationship research.

[2] Mark J. Welch explains that we can identify the rapid expansion of ethanol from 2007 to 2012, and the maturity of ethanol production system from 2012 to 2016. This consideration of periods will slightly affect the correlation between energy prices and grain prices.

[3] We check that there is a different property of data before and after the implementation of RFS. This could give us a hint that we need to adopt a different econometrics tool to analyze the price structure.

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